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Neuromorphic Computing

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INTRODUCTION

What is Neuromorphic Computing?

Neuromorphic computing refers to neural-inspired systems designed for non–von Neumann architectures that integrate principles from neuroscience, machine learning, AI, hardware design, and materials science. Initially focused on analog circuits mimicking biological neurons and synapses, the field has expanded to encompass a broad range of hardware and software systems. Core features of neuromorphic systems include co-located memory and computation, simple communication between neurons and synapses, and local learning capabilities. Many also exhibit spiking behavior, nonlinear dynamics, high connectivity, plasticity, robustness, and the ability to process noisy or incomplete data. These systems are typically event-driven, enabling low-power operation and emphasizing temporal dynamics. Their development requires interdisciplinary collaboration across neuroscience, computer science, engineering, and materials science.

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Current State of Neuromorphic Computing Research

Neuromorphic computing spans multiple disciplines, making it difficult to fully define due to diverse goals and approaches across neuroscience, computer science, engineering, and materials science. It lies on a spectrum of repurposable computing platforms, contrasting with synchronous von Neumann architectures through increased parallelism and asynchrony. One branch of research focuses on accelerating deep learning by creating hardware tailored to specific networks (e.g., CNNs) and training methods like backpropagation. These systems-often industry-developed (e.g., Google's TPU, Intel's Nervana Engine)-fit the neuromorphic definition but rely heavily on large labeled datasets, differing from other neuromorphic approaches.

Figure1: Spectrum of repurposable computing platforms [WSP: Hylton]

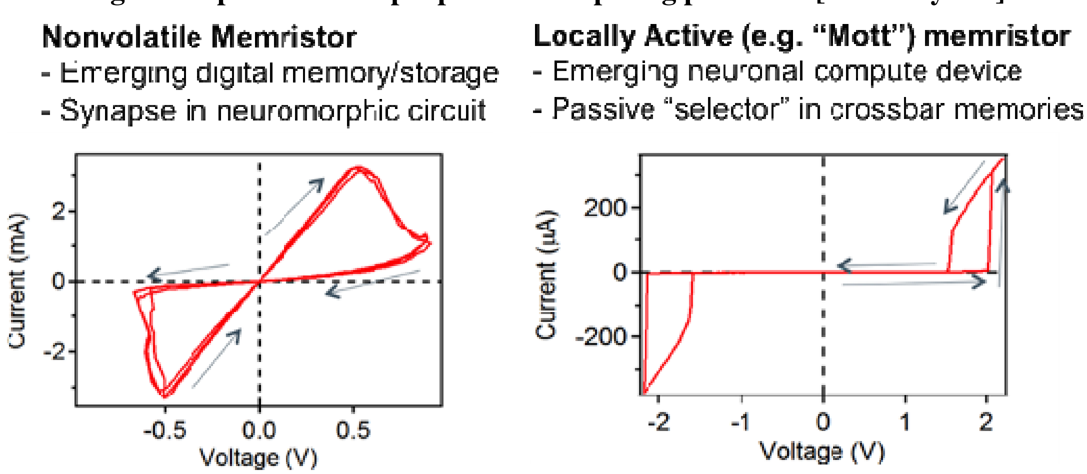

Figure 2: Two types of memristors that could be used in neuromorphic systems [Chua1971, WSP:Williams].

Advancements and Architectural Perspectives in Neuromorphic Computing

One of the most popular technologies associated with building neuromorphic systems is the memristor (also known as ReRAM). There are two general types of memristors: nonvolatile, which is typically used to implement synapses, and locally active, which could be used to represent a neuron or axon (Figure 2). Nonvolatile memristors are also used to demonstrate activation functions and other logical computations. Memristors used to implement synapses are often used in a crossbar.

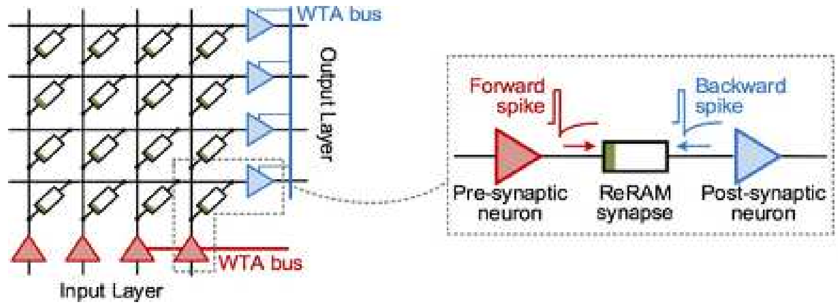

Figure 3: ReRAM used as synapses in a crossbar array [WSP:Saxena].

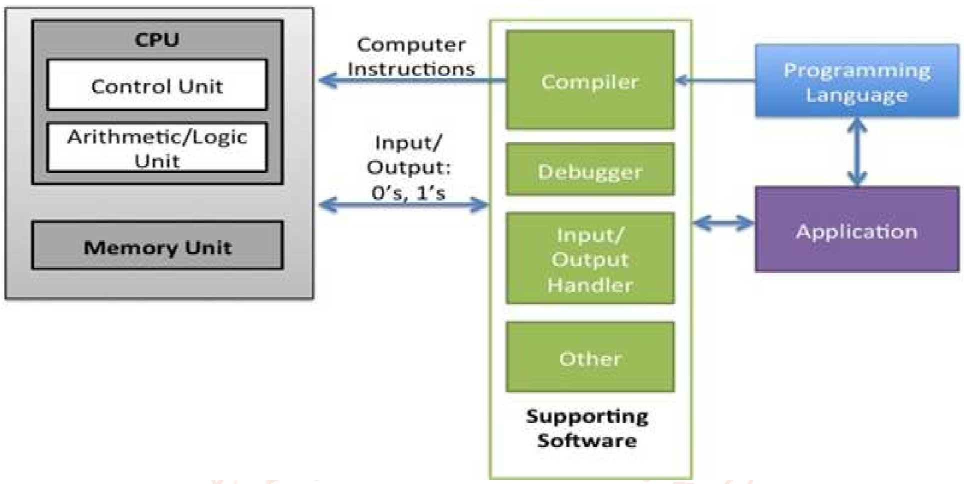

Figure 4: A von Neumann or traditional architecture from the computer science perspective

Open Issues

Neuromorphic computing includes researchers in fields such as neuroscience, computing, computer and electrical engineering, device physics, and materials science. The focus of the workshop was to identify the major questions from a computing perspective of neuromorphic computing or questions that can be addressed primarily by computational scientists, computer scientists, and mathematicians and whose solutions can benefit from the use of high-performance computing (HPC) resources.

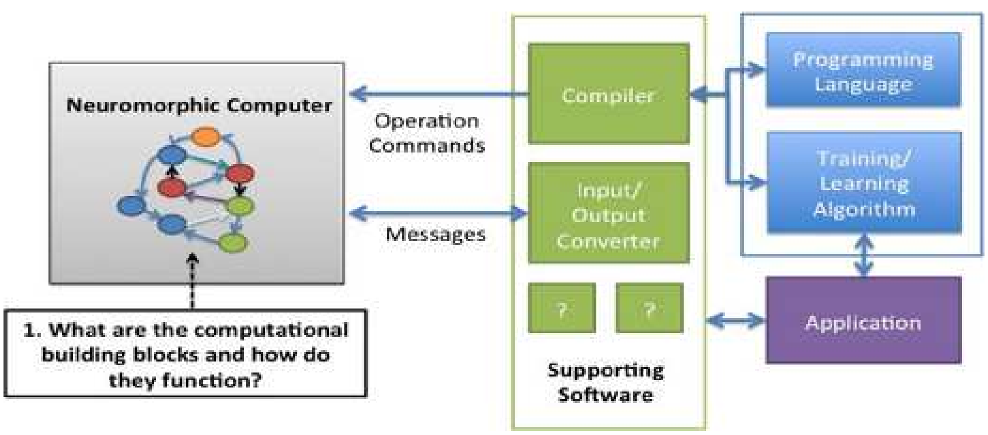

Figure 5: A potential neuromorphic architecture from the computer science perspective

Neuron, Synapse, and Biological Component Models in Neuromorphic Systems

Neuromorphic computing systems require careful selection of neuron and synapse models. Neuron models vary from simple threshold-based models like McCulloch-Pitts to complex biologically accurate ones like Hodgkin-Huxley. These models differ in biological realism, computational cost, and suitability for different applications.

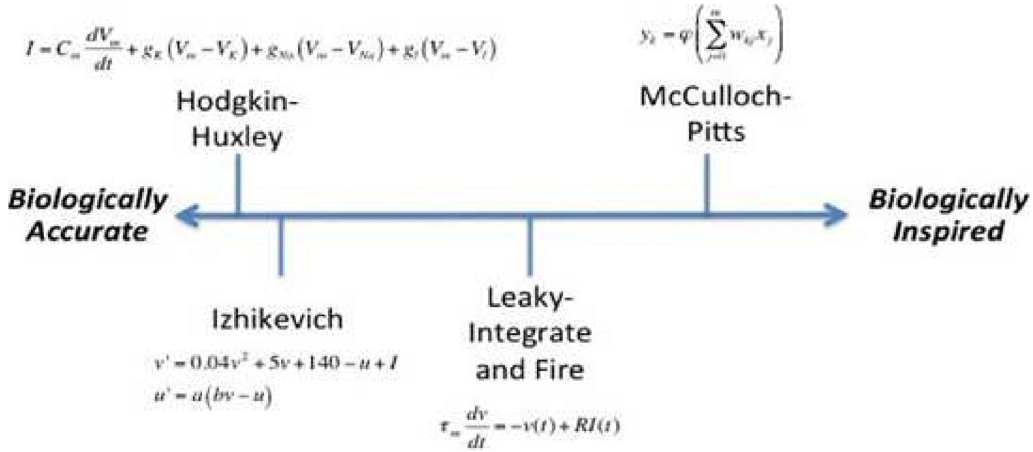

Figure 6: Example neuron models [Hodgkin1952, Izhikevich2003, Gerstner2002, McCulloch1943].

Neuromorphic Computing: Biological Realism vs. Functionality

One of the key research questions in neuromorphic computing is determining the level of complexity and biological realism necessary to achieve desired functionality. The models selected for a neuromorphic system should align with the system's ultimate goal. If the goal is biologically realistic simulations, the models must replicate biological systems as accurately as possible. However, the focus of this report is on the notion that the primary aim of neuromorphic architecture should be to create computationally efficient systems, not necessarily to mimic biological behaviour in detail.

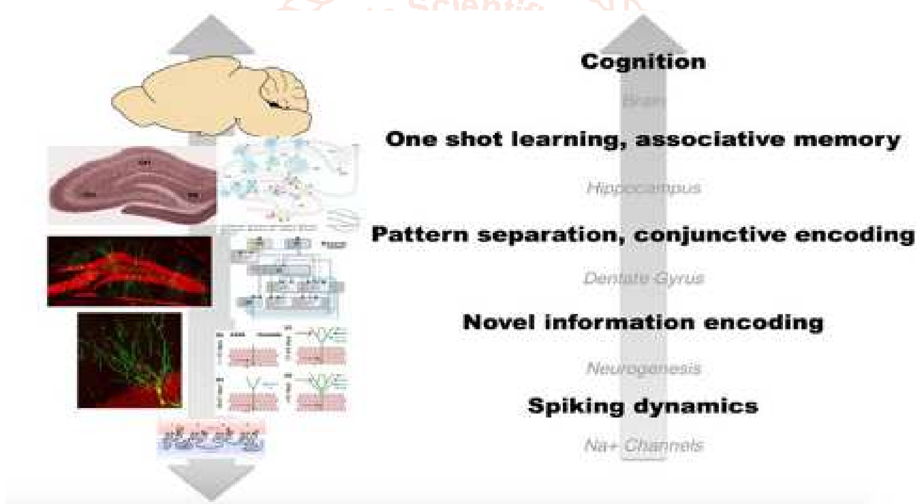

Figure 7: Levels of abstraction in biological brains and what functionality they may allow [WSP:Aimone].

LITERATURE REVIEW

[1] This paper introduces an in-memory neuromorphic computing (IMNC) chip that supports a hybrid topology of spiking and artificial neural networks (S/ANNs). The chip features a ring-based architecture optimized for sparse data flows, achieving high energy efficiency and accuracy. Experimental results demonstrate over 95% accuracy in tasks like voice activity detection and ECG anomaly detection, with a dynamic energy consumption of 0.43 pJ per synaptic operation. ir.pku.edu.cn.

[2] This work presents multilayer spintronic devices that function as both synapses and neurons in neuromorphic systems. The devices exhibit discrete resistance states due to magnetic domain wall dynamics, enabling multi-state memory and leaky integrate-and-fire neuron behavior. When integrated into a spiking neural network, the system achieves up to 90% accuracy on the MNIST dataset, showcasing potential for energy-efficient neuromorphic computing. IEEE Resource Center.

[3] This research explores the integration of photonic-electronic resonant tunneling diode (RTD) neurons with spiking flip-flop memory for neuromorphic computing. The proposed system utilizes spike-encoded information processing, leveraging the high-speed and low-power characteristics of RTD devices. This approach aims to enhance the performance and efficiency of neuromorphic systems.

[4] Yang discusses the use of integrated memristor networks to address the challenges of higher-

complexity neuromorphic computing. The paper highlights the potential of memristor-based architectures to emulate complex neural behaviors and facilitate scalable, energy-efficient computing systems. The integration of memristors offers advantages in terms of density and functionality for neuromorphic applications.

[5] NeuroSEE presents a neuromorphic processing framework designed for visual prostheses. By utilizing spike representation encoding and a bio-inspired spiking neural network model, the framework achieves significant energy efficiency improvements-up to 15 times lower power consumption compared to conventional CNN-based approaches. The system demonstrates high correlation with primary visual cortex responses, indicating its potential for prosthetic applications. IEEE EMBS

[6] This paper explores the application of deep learning techniques to train spiking neural networks (SNNs). It discusses the challenges and methodologies for adapting backpropagation and other optimization strategies to the spiking domain. The study provides insights into bridging the gap between traditional deep learning and spiking neural computation.

[7] Ottati et al. examine the trade-offs between spiking and non-spiking digital hardware architectures for deep learning acceleration. The paper provides a comparative analysis of energy efficiency, computational complexity, and performance, offering guidance on selecting appropriate architectures for specific applications.

[8] Sharma reviews the role of memristor-based networks in neuromorphic computing for artificial intelligence tasks. The article discusses the advantages of memristor devices in implementing synaptic weights and their impact on network dynamics, learning capabilities, and scalability. It also addresses challenges such as variability and non-linearity in memristor-based systems.

[9] Li et al. propose a multi-core neuromorphic system aimed at enhancing the energy efficiency of deep neural network training. The system leverages parallel processing and in-memory computing techniques to reduce power consumption while maintaining high performance. Experimental results demonstrate the system's effectiveness in training complex models with reduced energy requirements.

[10] Cauwenberghs discusses the design of neuromorphic circuits tailored for large-scale artificial intelligence applications. The paper covers aspects such as circuit architectures, scalability, and integration with existing AI frameworks. It emphasizes the importance of neuromorphic principles in achieving efficient and scalable AI systems.

[11] This work addresses the challenge of training quantized spiking neural networks (QSNNs) by proposing a cosine-annealed learning rate schedule combined with weight-independent adaptive moment estimation. The approach mitigates issues arising from gradient discontinuities during training, enabling QSNNs to escape local minima and achieve near-state-of-the-art performance on complex datasets. The authors provide empirical evaluations demonstrating the effectiveness of their method across multiple datasets.arXiv.

[12] This study explores the impact of dense and sparse mapping schemes on the performance of resistive random-access memory (RRAM) architectures in deep learning applications. The authors present a design space exploration methodology to quantify the benefits and limitations of these mapping schemes, considering factors such as power consumption, noise susceptibility, and network architecture. Their findings provide insights into optimizing RRAM-based accelerators for various deep learning tasks.arXiv.

[13] This resource provides an overview of neuromorphic computing, focusing on the integration of memristors in hardware design to emulate neural processing. It covers the transition from circuit-level implementations to algorithmic considerations, highlighting the potential of memristor-based systems in achieving energy-efficient and brain-inspired computing solutions. The content is aimed at researchers and practitioners interested in the interdisciplinary aspects of neuromorphic computing.

[14] This paper investigates the analog synaptic behaviors of carbon-based self-selective RRAM devices for in-memory supervised learning applications. The authors demonstrate the potential of these devices to emulate synaptic functions, such as weight update and retention, which are crucial for neuromorphic computing systems. Their findings contribute to the development of more efficient and scalable memristor-based learning systems.

[15] This research presents an implementation of a quantized convolutional neural network (CNN) on a parallel-connected memristor crossbar array, targeting edge AI platforms. The authors propose a radix-5 CNN architecture utilizing 1-bit memristors, achieving learning results comparable to high-precision models while reducing the area of the memristor crossbar array by half. Their work demonstrates the feasibility of deploying efficient

neural network models on memristor-based hardware for edge computing applications.

[16],[17],[18] This paper presents FGMSVM with one-against-one and maximum voting, using K-means clustering for noninvasive cardiovascular disease screening. It also explores a deep learning method for detecting five arrhythmia types via PPG and surveys approaches for noninvasive fetal oxygen saturation measurement using PPG.

[19],[20] This research presents a novel method to modify the current VCO for adjustable output voltage levels and develops an OP-AMP circuit using 22 nm FinFET technology with high-k gain for improved performance.

METHEDOLOGY

Spiking Neural Network (SNN) Architecture

Neuromorphic computing systems emulate the brain by using Spiking Neural Networks (SNNs), which process information through discrete spikes, closely resembling biological neural activity. This approach enables low-power, event-driven computation and offers improved temporal dynamics compared to traditional neural networks. Neurons activate only when input exceeds a threshold, communicating via timed spikes, ensuring energy is used only by active components. A notable example is IBM's TrueNorth chip, which simulates over one million neurons and 256 million synapses for tasks such as visual and pattern recognition.

Neuron and Synapse Modeling

Neuromorphic chips are composed of artificial neurons and synapses designed to replicate key biological functions, enabling complex learning, memory, parallelism, and adaptability-fundamental to bio-inspired intelligence. Neurons integrate incoming spikes and generate outputs, while synapses adjust signal strength based on learning rules such as Spike-Timing Dependent Plasticity (STDP). These functionalities are implemented using digital, analog, or mixed-signal circuits. A notable example is Intel's Loihi chip, which supports real-time, on-chip learning through programmable synaptic plasticity.

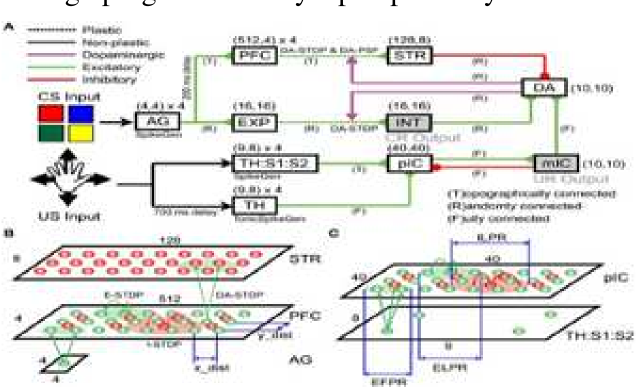

Fig 1.1.1: SNN Architecture

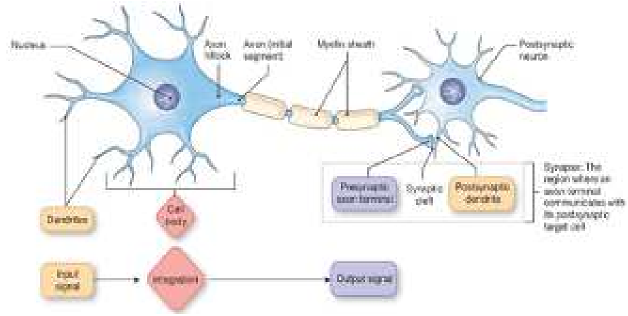

Fig 1.1.2: Neuron & Synapse Modeling

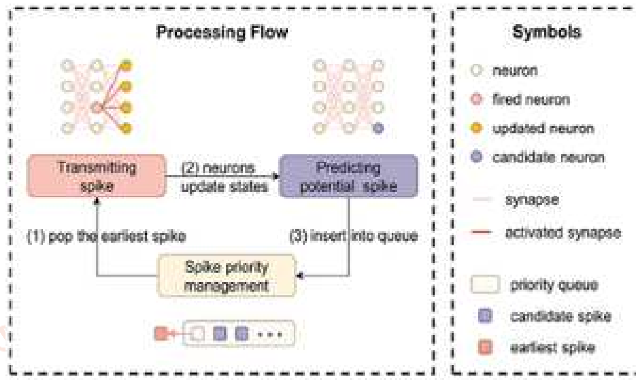

Fig 1.1.3: Event-Driven Communication

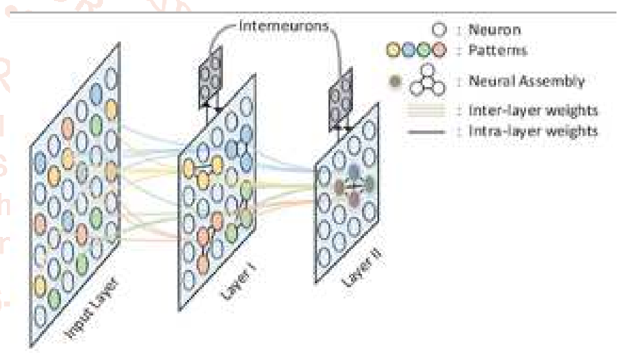

Fig 1.1.4: Hardware Implementation

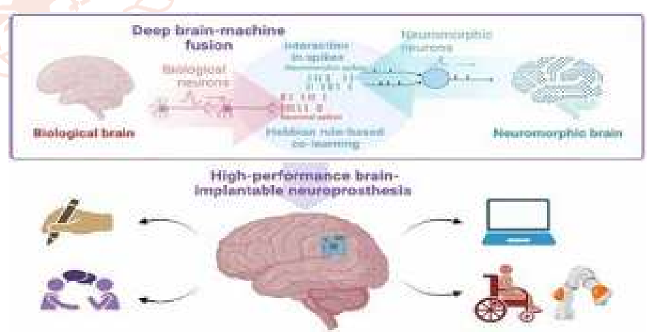

Fig 1.1.5: Neuromorphic Brain Fusion

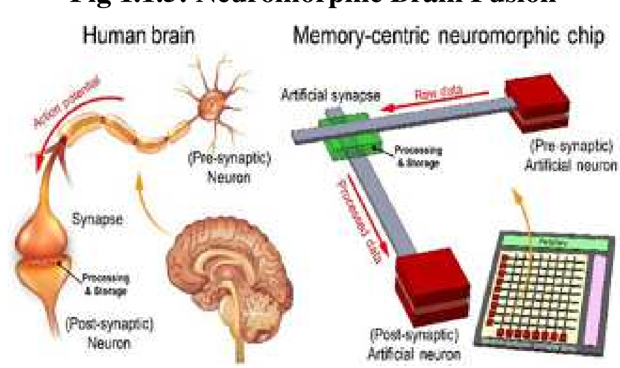

Fig 1.1.6: Neuromorphic Computing

Fig 1.1.1: SNN Architecture and Fig 1.1.2: Neuron & Synapse Modeling illustrate the core components of Spiking Neural Networks (SNNs), where neurons communicate via asynchronous spikes, mimicking biological brain activity. Neurons fire when a threshold is reached, and synapses adjust their strength based on learning rules like Spike-Timing Dependent Plasticity (STDP), enabling real-time adaptation. Fig 1.1.3: Event-Driven Communication and Fig 1.1.4: Hardware Implementation shift focus to the event-driven nature of neuromorphic systems, ensuring energy efficiency by triggering computation only during events. Hardware implementations using digital, analog, or mixed-signal circuits replicate neuron and synapse behavior for real-time, on-chip learning. Lastly, Fig 1.1.5: Neuromorphic Brain Fusion and Fig 1.1.6: Neuromorphic Computing highlight the integration of neuromorphic systems into practical applications like pattern recognition and decision-making, demonstrating the potential of bio-inspired, energy-efficient computing.

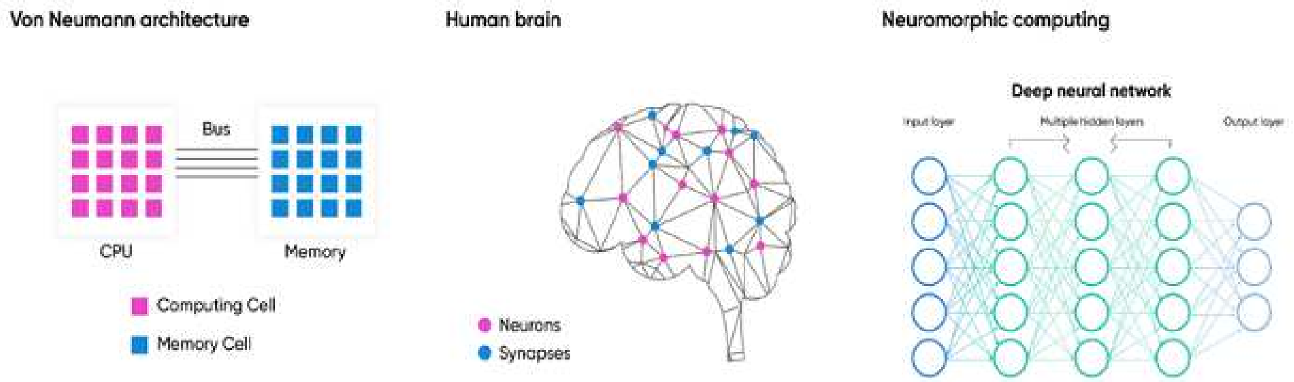

Fig: Neuromorphic Computing: The Future Brains of Computing

Neuromorphic computing is an innovative paradigm inspired by the structure and function of the human brain, aiming to revolutionize computing by creating systems that mimic biological neural networks. This approach utilizes specialized hardware, such as spiking neural networks (SNNs), which process information through discrete spikes, enabling energy-efficient, parallel, and event-driven computation. By integrating memory and processing, neuromorphic systems are designed to learn and adapt in real-time, offering significant advantages over traditional computing architectures in tasks that require cognitive functions, pattern recognition, and decision-making. With applications spanning from artificial intelligence to robotics, neuromorphic computing holds the potential to deliver scalable, low-power, and highly adaptive systems that can better emulate the brain's processing capabilities, ushering in the future of intelligent, bio-inspired computing.

CONCLUSION

In conclusion, neuromorphic computing represents a transformative approach to computing that draws inspiration from the brain's structure and function, offering a promising alternative to traditional von Neumann architectures. By leveraging spiking neural networks, event-driven communication, and bio-inspired learning rules, neuromorphic systems enable energy-efficient, parallel, and adaptive computation, making them well-suited for tasks such as pattern recognition, decision-making, and real-time learning. The ongoing advancements in hardware design, such as memristors and specialized chips like IBM's TrueNorth and Intel's Loihi, underscore the potential of neuromorphic systems to revolutionize fields ranging from artificial intelligence to robotics. As interdisciplinary research continues to evolve, neuromorphic computing is poised to unlock new possibilities in cognitive computing, offering scalable and efficient solutions that closely mirror biological processes and pave the way for the next generation of intelligent systems.

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